



# **Microwave Image Reconstruction of 3-D Dielectric Scatterers via Stochastic Optimization Approaches**

**By**

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# **CERTIFICATE OF AUTHORSHIP / ORIGINALITY**

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# ABSTRACT

The reconstruction of microwave images is generally considered as a nonlinear and ill-posed inverse scattering problem. Such problems are generally solved by the application of iterative numerical methods. However, the accuracy of images reconstructed by traditional methods is heavily dependent on the choice of the initial estimate used to solve the problem. Thus, with the aim to overcome this problem, this research work has reformulated inverse problems into global optimization problems and investigated the feasibility of solving such problems via the use of stochastic optimization techniques. A number of global inverse solvers have been implemented using different evolutionary strategies, namely the rivalry and cooperation strategies, and tested against a set of imaging problems involving 3-D lossless and lossy scatterers and different problem dimensions. Our simulation results have shown that the particle swarm optimization (PSO) technique is more effective for solving inverse problems than techniques such as the genetic algorithms (GA) and micro-genetic algorithms ( $\mu$ GA). In addition, we have investigated the impact of using different PSO neighborhood topologies and proposed a simple hybrid boundary condition to improve the robustness and consistency of the PSO technique. Furthermore, by examining the advantages and limitations of each optimization technique, we have proposed a novel optimization technique called the micro-particle swarm optimizer ( $\mu$ PSO). With the proposed  $\mu$ PSO, excellent optimization performances can be obtained especially for solving high dimensional optimization problems. In addition, the proposed  $\mu$ PSO requires only a small population size to outperform the standard PSO that uses a larger population size. Our simulation results have also shown that the  $\mu$ PSO can offer a very competitive performance for solving high dimensional microwave image reconstruction problems.

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# LIST OF ACRONYMS AND SYMBOLS

ABC	Absorbing boundary condition
ADI-FDTD	Alternating direct implicit finite-difference time-domain
BIM	Born iterative method
CT	Computed tomography
DBIM	Distorted Born iterative method
DT	Diffraction tomography
EM	Electromagnetic
FDTD	Finite-difference time-domain
FEM	Finite element method
FMM	Fast multipole method
GA	Genetic algorithm
GCPSO	Guaranteed convergence particle swarm optimizer
GLM	Gel'fand-Levitan-Marchenko
MGM	Modified gradient method
MLFMA	Multilevel fast multipole algorithm
MoM	Method of moment
MRTD	Multiresolution time-domain
NKM	Newton Kantorovich method
$OF$	Objective function
OUI	Object under investigation
PEC	Perfectly electrically conducting
PML	Perfectly matched layer
PSO	Particle swarm optimization
PSTD	Pseudospectral time-domain
RCS	Radar cross section
RMSE	Root mean square error
SNR	Signal-to-noise ratio
UCA	Uniform circular array
UWB	Ultra-wideband
$\mu$ GA	Micro-genetic algorithm
$\mu$ PSO	Micro- particle swarm optimizer
$\phi(\mathbf{r})$	Total phase
$\phi_0(\mathbf{r})$	Incident phase
$\phi_1(\mathbf{r})$	Scattered phase

$\overline{\mathbf{G}}(\mathbf{r}, \mathbf{r}')$	dyadic Green's function
$n_\delta$	Change in refractive index
$\psi(\mathbf{r})$	Total field
$\psi_0(\mathbf{r})$	Incident field
$\lambda$	Wavelength
$\mu$	Permeability
$\sigma$	Conductivity
$\omega$	Angular frequency
$\beta$	A parameter used to adjust the increment of the inertia weight
$\alpha$	Constant
$\varphi, \varphi_1$ and $\varphi_2$	Constants
$\rho(t)$	Scaling factor
$\Delta x, \Delta y$ and $\Delta z$	Dimensions of a FDTD cell
$a$	Radius of a homogeneous cylinder
$c_1$ and $c_2$	Acceleration constants
$D$	Dynamic range of the problem space
$\mathbf{E}$	Total electric field
$\mathbf{E}_{inc}$	Incident field
$\mathbf{E}_s$	Scattered field
$g_{best}$	Global best neighborhood topology
$g_{best}$	Best solution found by the entire swarm
$H$	Schema
$\mathbf{H}$	Total magnetic field
$k$	Wavenumber
$k$	Constriction factor
$L$	Length of the chromosome
$l_{best}$	Local best neighborhood topology
$m$	A parameter used to adjust the $\mu$ PSO repulsion
$N$	Problem dimension
$N_{bit}$	Number of bits per gene
$N_{chro}$	Number of chromosomes
$N_{gene}$	Number of genes per chromosome
$N_{i,best}$	Best solution found by the neighborhood of the $i^{\text{th}}$ particle
$N_{sub}$	Size of the sub-population
$O(\mathbf{r})$	Inhomogeneity
$P_{cross}$	Crossover probability
$p_{i,best}$	Best solution found by the $i^{\text{th}}$ particle
$P_{mut}$	Mutation probability
$r_1, r_2$ and $r_3$	Uniformly distributed random variables in the range of $[0,1]$
$r_3$	Uniformly distributed random variable in the ranges of $[1, N_{chro}]$
$r_4$	Uniformly distributed random variable in the ranges of $[1, L]$

$rep_i$	Amount of repulsion experienced by the $i^{\text{th}}$ particle
$s_{th}$ and $f_{th}$	threshold values for the success and failure, respectively
$u_{\max}$	Maximum wave phase velocity
$V_i(t)$	Velocity of the $i^{\text{th}}$ particle
$V_{\max}$	Maximum velocity
$w$	Inertia weight
$w_{\text{init}}$	The initial value of the inertia weight
$w_{\max}$	Maximum allowed value for the inertia weight
$X_i(t)$	Position of the $i^{\text{th}}$ particle
$\varepsilon$	Permittivity